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# Estimating Menu Costs in Electronic Markets

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# ESTIMATING MENU COSTS IN ELECTRONIC MARKETS

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## Abstract

*Menu costs, or price adjustment costs, refer to the total cost of changing the price of a product, which includes the physical cost of making the change as well as the managerial cost of making the price change decision. Prior work has presumed that online retailers face no menu costs, potentially leading to Bertrand competition and the Law of One Price. However, little empirical evidence exists to assess the assumption. The objective of this research is therefore to empirically assess the magnitude of menu costs faced by online retailers. Using a nine-month product-level price and demand data from Amazon, we infer menu costs based on the retailer's price change decisions. A key challenge in this estimation is that price change decisions are driven by changes in a retailer's expectation of future demand, which is not directly observable by researchers. We use statistical methods to infer expected demand from realized demand, thus identifying the magnitude of price adjustment cost econometrically. We find that online retailers face non-negligible menu costs, representing about 0.2% of their gross revenues. Our results also reveal that menu costs at online retailers exhibit unique characteristics. Compared with prior studies in physical retailers, the result shows that online retailers incur significantly higher menu costs per price change, but the costs account for a lower proportion of the total revenue. We attribute this phenomenon to the scale economies of online retailers.*

**Keywords:** Electronic Commerce, Menu Costs, Product Variety, Web Based Retailers, Online Price Competition.

## Introduction

In the growing literature on the economics of electronic commerce, an often-mentioned fact is that online markets reduce “frictions” in the economy since retailers can freely obtain competitive pricing information. A natural consequence of this is that competing firms continuously monitor each other’s prices and have the information required to make price adjustments instantaneously.

Nevertheless, information access alone does not guarantee a frictionless market. An important requirement towards establishing such a market is the need for retailers to act upon such information and adjust prices without having to incur substantial costs in the process. Prior academic work has used a variety of techniques and methods to study pricing processes and the cost of price adjustment incurred by firms in order to improve our understanding of how firms set and adjust prices. In this stream of literature, such costs have usually been defined as menu costs and they consist of both the physical as well as the managerial costs of changing prices. These methods include surveys (e.g. Blinder et al. 1998), field studies (e.g. Levy et al. 1997) and econometric analysis (e.g. Slade 1998).

Lessons from physical markets show that price adjustment is a difficult, costly and time-consuming process and that changing prices “is a complex process, requiring dozens of steps and a non-trivial amount of resources” (Levy et al. 1997, p. 792). Thus, retailers need to incur substantial price adjustment costs to implement price changes. These costs include physically printing price labels, affixing it to retail products, updating POS systems for price changes, correcting errors and supervising these price change activities (Levy et al. 1997). Besides these factors, there are substantial managerial costs involved as well (Zbaracki et al. 2004). To set and adjust prices effectively, firms need to gather and analyze data that may be in different parts of the organization. They need the ability to assess a wide variety of market factors, from costs to customer segments, to estimating market demand, to understanding customer psychology, to anticipating competitors’ reactions and so on. They also need organizational structures and processes supporting these activities. Further, one needs to add the complexities of firms selling multiple products through multiple distribution channels, and to multiple customers. Consistent with these aspects, recent empirical studies of price adjustment processes conclude that the price adjustment cost associated with these processes may be significant in many offline markets across industries (Levy et al. 1997, Slade 1998, 1999).

Theoretical studies have shown that the presence of price adjustment cost has significant implications for both micro and macro economic structures (Blanchard and Kiyotaki 1987; Mankiw 1985). Indeed, Mankiw (1985) argued that the cost to a monopolistic competitive firm of a slightly mis-set price is only of a second order. Small price adjustment costs are then enough to induce significant price rigidity in markets. The price rigidity creates price dispersion among retailers. It also leads to market transactions taking place at non-clearing prices, resulting in market fluctuation and the need for government intervention. Understanding the nature of the menu costs and measuring its magnitude therefore has important implications for business strategies and public policies.

Prior empirical studies on menu cost largely focus on supermarket chains and other physical retail stores that require frequent and labor-intensive price changes. Naturally, the measurement of price adjustment cost emphasizes physical labor costs (Levy et al. 1997). Supermarket managers had to consider these kinds of costs because of the pricing task they face: on an average, they carry about 25,000 different products, and each week they change the prices of about 4,000–5,000 of them. Lee et al. (2006) find that (1) a supermarket chain facing higher price adjustment cost (due to item pricing laws which require a separate price tag on each item) changes prices 2.5 times less frequently than the other four chains; (2) within this chain, the prices of products exempt from the law are changed over three times more frequently than the products subject to the law. In aggregate, menu costs are found to account for between 0.5 and 0.7 percent of a retailer’s revenue (Levy et al. 1997, Golosov and Lucas 2007).

In contrast to the above, online retailers face a different environment. With no price labels to print or affix, and centralized systems for price changes, there is very little physical labor cost involved compared to the quintessential example given in the offline market where restaurant managers incur costs of altering menus periodically with new prices. Brynjolfsson and Smith (2000) found that Internet retailers make much smaller price changes than brick-and-mortar retailers do and argued that this was due to lower price adjustment cost. The reduction in price adjustment cost demands online retailers to be more nimble in responding to competitor price changes as well as in responding to demand and supply fluctuations.

While the internet environment has eliminated much of the physical costs associated with price adjustments, online retailers still face the management costs to make price adjustment decisions. As online retailers carry millions of SKUs, identifying the products that need price changes and deciding the magnitude of each price

change is a daunting task which requires careful analysis from the management. Moreover, online retailers face a complicated landscape with a large number of competitors, whose activities need to be monitored and analyzed in making price decisions. As a result, price adjustment cost for online retailers could be substantial due to the managerial costs of decision making. Indeed, Zbaracki et al. (2004) show that the managerial components of the cost of price adjustment are more than six times the physical costs associated with changing prices. A number of recent studies on online retailers shed more lights on this subject. Bergen, Kauffman and Lee (2005) find significant price rigidity for online retailers. The two main online book retailers, Amazon and BN.com change prices less than once every 90 days, a surprising low frequency for online retailers. It is not clear what exactly causes the observed price stickiness. The authors offer multiple potential explanations since the findings could reflect the presence of substantial price adjustment cost online or it could imply that online retailers face very low demand variation. These studies provide a glimpse of the possible presence of menu costs in online environment. Identifying the magnitude of price adjustment cost of these online retailers seems like a natural next step towards improving our understanding of the structure of online markets.

The objective of this paper is therefore to provide the first study that econometrically estimates and quantifies the magnitude of menu costs faced by firms in electronic markets. We explicitly model the online retailer's decision-making process for price changes and infer the price adjustment cost from online retailers' actual price change decisions. Our model takes into account that price change decisions at online retailers are mainly driven by demand shocks caused by competitive actions and other exogenous events that affect consumer demand. We fit an explicit optimizing menu-cost model of price dynamics developed by Dixit (1991) and Hansen (1999) to observed data. Our result reveals that that online retailers face non-negligible menu costs, accounting for 0.2% of retailers' gross revenue.

We also find that menu costs at online retailers exhibit some unique characteristics. First, menu costs per price change are quite substantial. Contrary to common wisdom, our results reveal price adjustment costs ranging from \$10.97 to \$ 11.11 per price change, significantly higher than the menu costs found in studies of offline grocery stores and retailers. We attribute the higher costs to online retailers' large scale operations and their exposure to a much more complex competitive environment than that faced by typical grocery stores or supermarket chains. Second, we find that, due to economies of scale, menu costs account for a much smaller proportion of total sales in online retailers. This finding supports the earlier conjecture that online retailers are more efficient at price changes. The combination of these two aspects provides us with a better understanding of the nature of menu costs for online retailers. It suggests that lower menu costs at online retailers are primarily due to economies of scales instead of reduction in physical costs in price changes. It also shows the importance of making a distinction between menu costs for individual price changes for individual products and total menu costs as a percentage of revenues.

The rest of the paper is as follows. Section 2 describes a simple theoretical model for price change decisions. We then present the data and empirical approach in Section 3. Section 4 offers results and analysis of online price adjustment cost. Conclusion and limitations are discussed in Section 5.

## Theoretical Model

We consider price change decisions at a multi-product online retailer. A number of factors could motivate the retailer to change price. Macroeconomic shocks such as inflation have been cited one of the main causes for price changes over the long horizon (Kashyap 1995). In the short term, unexpected changes in wholesales costs and labor productivity could also prompt a retailer to change prices (Davis and Hamilton 2004, Golosov and Lucas 2007). In this research, we focus on another key cause for price changes at retailers - demand shocks. Demand shocks refer to changes in consumer demand for a retailer's products due to competitors' activities, consumer preference shifts or other exogenous factors. As a result, the retailer needs to adjust prices accordingly to maximize its profit. Blinder (1991) shows that majority of firms he surveyed cite demand shocks as the number one reason for price changes. To model price decision under demand fluctuation, we assume that the retailer faces a linear demand function of the following kind:

$$q_i(t) = B_i X_i(t) - b_i p_i(t) \quad (1)$$

where  $X_i(t)$  is a vector of observed and unobserved exogenous factors that influence demand for product  $i$  at the retailer.  $b_i p_i(t)$  represents the impact of the retailer's price decision. Equation (1) separates consumer demand into two components: exogenous demand  $B_i X_i(t)$  and self-price effect  $b_i p_i(t)$ .

The retailer's objective is to set price for each time period to maximize its total profit. In an economy without menu costs, the retailer can change prices for each period without incurring any costs. The optimal price series  $p_i^*(t)$  in this case is the sequence of individual prices that maximize profit for each time period  $t$ . We note that price decisions always precede the realization of the exogenous influence  $B_i X_i(t)$ . This requires the retailer to set price decisions based on expectation. To operationalize the decision process, we assume that the retailer makes price decision for next time period  $t+1$  at the end of the current period  $t$ . The optimal price for period  $t+1$  can therefore be expressed as follows:

$$p_i^*(t+1) = \arg \max_{p_i} (p_i - c_i) E_t(q_i(t+1)) = \left( \frac{B_i E_t(X_i(t+1)) + c_i}{2b_i} \right) \quad (2)$$

$E_t(B_i X_i(t+1))$  in the above question represents the retailer's one-period-ahead expectation of exogenous demand factors for time period  $t+1$ , and the retailer's optimal price has a linear relationship with the expected demand.

The retailer forms expectation based on what he observed in the current period  $t$ . A variety of events could influence the expectation. A competitor may decide to change its price, reducing the underlying demand for the retailer's product. Consumer tastes may shift, leading to either an increase or decrease in the underlying demand. Substitute or complimentary products may be introduced into the market during the period, influencing the underlying demand. These events change not only demand for the current time period but also demand in future periods. However, not all demand events in period  $t$  influence the retailer's expectation for the next period. For example, bad weather may keep people indoors thus temporarily increasing underlying demand for the online retailer. This type of demand changes is transitory and does not influence the retailer expectation for future demand.

The above discussion suggests that exogenous demand changes that happen in the current period can be classified into two types: permanent demand changes and transitory demand changes. Permanent demand changes influence consumer demand in time period  $t$  and beyond, while transitory demand changes only influence current consumer demand in time period  $t$ . An important task for the retailer is to distinguish the two types of events in forecasting future demand. While some of the demand events (e.g. competitor pricing) can be directly observed by the retailer, many other factors (e.g. shift in consumer sentiments) can not. To address the problem, we assume that the retailer uses statistical approach to distinguish the two types. We also assume that the two types of demand changes are independent of each other and both follow a normal distribution. This leads to a random walk plus noise model (Chatfield 2003) for the exogenous demand:

$$B_i X_i(t+1) = \tau_i(t+1) + e_i(t+1); e_i(t+1) \sim N(0, \sigma_{ie}) \quad (3)$$

$$\tau_i(t+1) = \tau_i(t) + d_i(t+1); d_i(t+1) \sim N(0, \sigma_{id}) \quad (4)$$

In Equation (3),  $B_i X_i(t+1)$  represents exogenous demand for the next period. It consists of two components:  $\tau_i(t+1)$  stands for accumulation of permanent demand changes up to time period  $t+1$ , and  $e_i(t+1)$  represents transitory demand changes for that period. Since permanent demand changes  $d_i(t+1)$  follow normal distribution,  $\tau_i(t+1)$  must follow a random walk process. We also note that when the retailer makes the decision at the end of period  $t$ , neither  $d_i(t+1)$  nor  $e_i(t+1)$  has been realized. Given that their expected values are zero, the retailer's expectation for next period's underlying demand simply equals to the permanent demand level  $\tau_i(t)$  in the current period:

$$E_t(B_i X_i(t+1)) = E_t(\tau_i(t)) + E_t(d_i(t+1)) + E_t(e_i(t+1)) = \tau_i(t) \quad (5)$$

Substitute (5) into (2), the optimal price process can be expressed as follows:

$$p_i^*(t+1) = \arg \max_{p_i} (p_i - c_i) E_i(q_i(t+1)) = \left( \frac{\tau_i(t) + c_i}{2b_i} \right) \quad (6)$$

Equation (6) indicates that optimal price for next period is a linear function of cumulative permanent demand changes up to the current period. Since  $\tau_i(t)$  follows a random walk process,  $p_i^*(t)$  also follows a random walk process. The magnitude of price change can be directly calculated from (6) by comparing the optimal price at time period  $t$  with that at time period  $t-1$ .

$$\Delta p_i(t+1) = p_i^*(t+1) - p_i^*(t) = \frac{d_i(t)}{2b_i} \quad (7)$$

Equation (7) reveals that the retailer changes its price for the next period if and only if there are permanent demand changes in the current period.

The above analysis identifies the optimal price decisions for the retailer when there are no menu costs. The situation is different when the firm faces menu cost. In this case, it becomes worthwhile for the firm to wait and see rather than revising price every time when there is a permanent demand change. This is due to two reasons. First, for small changes in permanent demand, it may no longer be profitable for the firm to change its price given the presence of menu costs. Second, the firm realizes that permanent demand changes constantly. A change today could be offset in the next period thereby reducing the necessity of a price change.

These reasons imply that in the presence of menu costs, retailers may not always charge the optimal price  $p_i^*(t+1)$  according to equation (6). While the retailer realizes that any deviation from the optimal price results in a loss, it is willing to wait until the expected loss from waiting exceeds the price adjustment cost. The magnitude of the loss can be estimated by determining the difference between its profit under the optimal price  $p_i^*(t+1)$  and the profit under the actual price  $p_i(t+1)$ . We apply Taylor's series to the retailer's profit function when it charges a price that is different from the optimal price. After simplification and substitution we have the following equation.

$$E_i(\pi_i(p_i(t+1), t+1)) - E_i(\pi_i(p_i^*(t+1), t+1)) = -E_i(b_i(p_i(t+1) - p_i^*(t+1))^2) \quad (8)$$

Equation (8) indicates that the expected loss from deviating from the optimal price depends on consumers' price sensitivity (the 'b' parameter) and the absolute magnitude of the deviation between the actual price and the optimal price  $(p_i(t+1) - p_i^*(t+1))^2$ . In the absence of menu costs, maximizing profit is equivalent to minimizing  $E_i(b_i(p_i(t+1) - p_i^*(t+1))^2)$ . So the retailer needs to keep changing its price to be in tune with the optimal price. However, the presence of price adjustment cost requires the retailers to consider both the loss of deviating from the optimal prices and the cost of adjusting prices.

Based on prior empirical evidence, we model the menu costs as a fixed cost for each price change and denote the cost as  $g$ . For example, Blinder, et al. (1998) find support for the fixed cost model in their survey responses. Levy et al. (1997) also suggest that there is little evidence of convexity in the physical costs of the price adjustments they studied. Further, Slade (1998) analyzes the fixed and variable components of menu costs and finds that fixed costs constitute 94% of the total cost of a price change.

The retailer's objective is to minimize the total expected loss of temporal deviation from the optimal price and the menu cost (Dixit 1991). Note that the nature of menu cost is different from deviation loss. While deviation loss is a flow cost that accumulates overtime, price adjustment cost is discrete that occurs only when price is changed. Let  $t_{i1}, t_{i2}, \dots$  be the time periods at which the firm decides to change prices on product  $i$  and let  $p(t_{i1}), p(t_{i2}), \dots$  be the prices associated with each price change. The retailer's objective function is to choose  $t_{i1}, t_{i2}, \dots$  to change its price in way that minimizes the following total expected cost:

$$E \left\{ \sum_{j=1}^{\infty} \left[ \left( \sum_{t_{ij}}^{t_{ij}} b_i [p_i(t_{i,j-1}) - p_i^*(t)]^2 dt \right) + g e^{-rt_{ij}} \right] \right\} \quad (9)$$

The first part of the summation represents the expected net present loss to the firm of being away from its optimal price, where  $e^{-rt}$  is the discounting factor. The second item in the equation represents the present value of the menu costs, where  $g$  is the menu cost for each price change and  $t_{ij}$  represents the time periods that the retail change price on product  $i$ . Equation (9) presents an optimal control problem where pricing decisions are made by the retailer continuously.

Dixit (1991) provides a solution to equation (9) in a continuous setting. His results suggest that the optimal solution for the retailer is to change price if and only if the absolute difference between the prevailing price  $p_i(t)$  and the optimal price for the next period  $p_i^*(t+1)$  is larger than a constant given by:

$$|p_i^*(t+1) - p_i(t)| \geq \left( \frac{6g\sigma_{ip}^2}{b_i} \right)^{1/4} \quad (10)$$

where  $\sigma_{ip}^2$  represents the variance of the optimal prices of product  $i$  over time. Given equation (6), we know that the variance of the optimal price has a linear relationship with variance of the permanent changes of underlying demand. More specifically, we have

$$\sigma_{ip}^2 = \frac{\sigma_{id}^2}{4b^2} \quad (11)$$

Substitute (11) into (10), the threshold condition for price change is:

$$|p_i^*(t+1) - p_i(t)| \geq \left( \frac{6g\sigma_{id}^2}{4b_i^3} \right)^{1/4} \quad (12)$$

The above equation lends itself very easily to comparative statics. If menu cost increases, it is immediate that the range of values over which prices remain the same widens. Intuitively, if it is more expensive to adjust the price, a retailer finds it desirable to postpone the price adjustment decision, leading to a wider band. Secondly, if consumer price sensitivity increases, it means that the profit loss from deviating from the equilibrium is greater and therefore, the costs of the wait-and-see attitude increase. As a result, the band decreases. Finally, an increase in uncertainty of underlying demand expands the band. This is because a large amount of uncertainty reduces the value of price changes since the optimal price will quickly move from the current price. This reduces the retailer's incentive to change prices and lead to a larger range over which prices are sticky.

## Empirical Framework

Equation (12) provides a framework to estimate the price adjustment costs  $g$  from observed magnitude of price change. The equation indicates that price does not change when the difference between optimal price in the next period and the current price is smaller than the threshold. Menu costs can therefore be inferred from the retailers' decisions given the current prices and the estimated optimal price series. To convert equation (12) into an empirical model, we use an approach similar to Davis and Hamilton (2004) to assess retailers' price change decisions. We note that there are likely to be noises in the retailer's decision making process. Therefore we can not perfectly predict the retailer's price change decisions given the prevailing price and the optimal price for the next period. However, we can use statistical approaches to estimate the retailer's probability of making price changes. We assume that the noises in the retailer's decision process follow a normal distribution with zero mean and standard deviation  $\sigma_\epsilon$ . The probability that the retailer changes price in the next period given the current price  $p(t)$  and the optimal price for the next period  $p_i^*(t+1)$  can be expressed as follows:

$$\begin{aligned}
 h(p_i^*(t+1), p_i(t)) &= \Pr \left( \left| p_i^*(t+1) - p_i(t) \right| \geq \left( \frac{6g\sigma_{id}^2}{4b_i^3} \right)^{1/4} \right) \\
 &= \Pr \left( p_i^*(t+1) - p_i(t) \geq \left( \frac{6g\sigma_{id}^2}{4b_i^3} \right)^{1/4} \right) + \Pr \left( p_i^*(t+1) - p_i(t) < -\left( \frac{6g\sigma_{id}^2}{4b_i^3} \right)^{1/4} \right) \\
 &= \Phi \left( \frac{p_i^*(t+1) - p_i(t) - \left( \frac{6g\sigma_{id}^2}{4b_i^3} \right)^{1/4}}{\sigma_\varepsilon} \right) + 1 - \Phi \left( \frac{p_i^*(t+1) - p_i(t) + \left( \frac{6g\sigma_{id}^2}{4b_i^3} \right)^{1/4}}{\sigma_\varepsilon} \right)
 \end{aligned} \tag{13}$$

Menu costs  $g$  can be inferred from observed price change decisions based on maximum likelihood method. The log likelihood of observing a particular sequence of price changes  $\{x_1, \dots, x_T\}$  equals to

$$\sum_{t=0}^{T-1} \{x_{t+1} \log h(p_i^*(t+1), p_i(t)) + (1 - x_{t+1}) \log(1 - h(p_i^*(t+1), p_i(t)))\} \tag{14}$$

Identification of menu costs requires finding  $g$  that maximizes Equation (14). The maximization is straightforward but requires knowledge of optimal price for the next period  $p_i^*(t+1)$ , prevailing price  $p_i(t)$ , variance of permanent demand events  $\sigma_{id}^2$  and consumer price sensitivity  $b_i$ . While  $p_i(t)$  is directly observable to researchers, all other information needs to be estimated from the realized demand process. This requires a two-step approach in estimating menu costs. We first estimate the three parameters from the demand process and then estimate menu costs given the retailer's price change decisions.

### Demand Process

Equations (1) and (3) suggest that the retailer expects next period demand are influenced by two factors. The first factor is permanent and transitory changes in underlying demand, modeled by a random walk plus noise process. The second factor is the self-price effect. Combination of equation (1) and (3) suggests that demand realized for the next period can be written as follows:

$$\begin{aligned}
 q_i(t+1) &= \tau_i(t+1) + e_i(t+1) - b_i p_i(t+1) \\
 \text{where} \\
 \tau_i(t+1) &= \tau_i(t) + d_i(t+1); \\
 d_i(t+1) &\sim N(0, \sigma_{id}) \\
 e_i(t+1) &\sim N(0, \sigma_{ie})
 \end{aligned} \tag{15}$$

The above equation is a form of unobserved component model (UCM) that can be directly estimated using standard statistical software. The estimation separates demand processes into permanent demand level  $\tau_i(t)$  that influences demand in future time period and transitory demand changes that only influence current period demand. The decomposition of demand allows us to estimate optimal price level  $p_i^*(t+1)$  for every time period using Equation (5). The UCM estimation also provides estimation of variance of permanent demand changes ( $\sigma_{id}$ ) and price sensitivity  $b_i$  for each product.

One caveat in the above estimation is that we do not actually observe consumer demand  $q_i(t)$  in our data. Instead, we observe daily sales rank of each product, and we need to convert these sales ranks into quantities. Two



recent papers address this problem by providing a way to map the observable Amazon.com sales rank to the corresponding number of books sold. In both cases, the authors find a stable relationship between the ordinal sales rank of a book and the cardinal number of sales, using the following Pareto relationship:

$$Quantity = \delta \cdot Rank^\theta \quad (16)$$

Chevalier and Goolsbee (2003) estimate the parameters of this equation for books by associating demand data with sales rank on the Wall Street Journal best-seller list, and by independently conducting a purchasing experiment on one book whose actual weekly demand was known to them. Observing the extent to which Amazon sales rank reacted to their purchases, they estimate  $\theta = -0.855$ . In their study of the impact of used book markets on new book sales, Ghose, Smith and Telang (2006), use  $\theta = -0.871$ . For our study, we continue to use the same parameter for imputing  $q_i(t)$ .<sup>1</sup>

## Data and Analysis

We estimate our model using a panel data set of product prices and sales ranks on Amazon. The data was collected using automated Java scripts that accessed and parsed HTML and XML pages from Amazon between September 2005 and March 2006. The panel includes daily data on 3101 books drawn from all major book categories. Specifically, these products include a mix of best sellers, new releases, random selected titles and less popular books selected from the different genres such as fiction, non-fiction, business, textbooks, computer books and so on. Each observation contains the date of data collection, the product's list price, its retail price, its sales rank (which serves as a proxy for units of demand, as described later) and the date the product was released into the market. The summary statistics of our data are in Table 1. It shows a significant amount of variation in the sample we use, covering a wide range of books with different online prices, sales ranks, and release dates. Table 1 also provides summary statistics on price change activities. These statistics show that the retailer does not change price often and provide a glimpse into the potential presence of menu costs. The probability of price change on a given day is about 0.7%. That means, on average, a prices stay for 143 days before being changed. This level of price rigidity is consistent with what is reported in Lee and Kauffman (2005).

## Empirical Results

Before we estimate equations (15) and (14), we first assess the presence of transitory demand changes. If there are no transitory demand changes, then there will no need to decompose demand and the best predictor for tomorrow's demand would be today's realized demand. To identify the presence of transitory demand changes, we examine autocorrelation of the first difference of realized demand. A transitory change in demand today will offset by a change in the opposite direction tomorrow. This leads to a negative autocorrelation in demand changes. On the other hand, a permanent demand change today does not lead to a reversion tomorrow, suggesting a zero autocorrelation. Formally, demand changes between period  $t-1$  and period  $t$  can be written as follows

$$\Delta q_i(t) = q_i(t) - q_i(t-1) = d_i(t) + e_i(t) - e_i(t-1) - b_i \Delta p_i(t) \quad (17)$$

The underlying demand  $d_i(t) + e_i(t) - e_i(t-1)$  is auto correlated because of the reversion of transitory demand changes from the previous period. To see this, let  $\eta_i(t) = d_i(t) + e_i(t) - e_i(t-1)$ , we have

$$Cov(\eta_i(t), \eta_i(t-1)) = Cov(-e_i(t), e_i(t)) = -\sigma_{ie}^2. \quad (18)$$

Equation (18) indicates that the first difference of realized demand is auto correlated if and only if there are transitory demand changes. Also note that  $Var(\eta_i(t-1)) = \sigma_{id}^2 + 2\sigma_{ie}^2$ . This suggests that in a regression of  $\eta_i(t)$  on  $\eta_i(t-1)$ , the coefficient on  $\eta_i(t-1)$  would be

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<sup>1</sup> Ghose and Sundararajan (2006) extend existing methods for imputing demand from Amazon's sales rank information, and provide the first calibration of this relationship for the software industry. They find  $\theta = -0.828$  and  $\log[\delta] = 8.352$ . These studies thus find a high degree of consistency in the values of the Pareto slope parameters.

$$\beta_i = \frac{\text{Cov}(\eta_i(t), \eta_i(t-1))}{\text{Var}(\eta_i(t-1))} = -\frac{\sigma_{ie}^2}{\sigma_{id}^2 + 2\sigma_{ie}^2} \quad (19)$$

Table 2 shows the result of this regression.<sup>2</sup> The estimation suggests that the coefficient is negative and significant, indicating a significant presence of transitory demand changes. We can directly derive transitory demand change's impact on demand variance given equation (19). Note that the total variance in day-to-day demand change is  $\sigma_{id}^2 + 2\sigma_{ie}^2$ , the proportion of variance due to transitory demand change is equivalent to  $\frac{2\sigma_{ie}^2}{\sigma_{id}^2 + 2\sigma_{ie}^2}$ , i.e.  $-2\beta_i$ . Given the result from Table 2, we note that 74% of variance in day-to-day demand change is due to transitory demand changes. Table 2 shows the necessity to separate permanent demand changes from transitory demand changes. For each book included in the dataset, we estimate its daily permanent demand level, variance of permanent demand changes and consumer price sensitivity for each book using equation (15).

Once we obtain the three variables for each book from equation (15), we use the variables to estimate equation (16). Column 1 in Tables 3 presents the results of the estimation. The estimation shows a menu cost of \$11.11. To check for robustness, we also consider the possibility that discreteness of price changes could be due to consumers' lack of attention to small price changes. We revise equations (13) and (14) to take into accounts of two potential attention thresholds: 10 cents and 50 cents. The results are reported in Column 2 and 3 in Table 3. We find that the estimated menu costs are consistent at about \$11 per price change. The menu cost on Amazon merits comparison with earlier price adjustment cost estimations in offline markets for grocery stores and supermarkets. Levy et. al. (1997) study the detailed process of price changes in a supermarket chain and directly estimate its cost components. They find that price adjustment cost per change is about \$0.52. Slade (1998) and Aguirregabiria (1999) also study the supermarket industry. They estimate the price adjustment cost as one of the structural components in either a single or multiple agent model. Slade (1998) finds that the average cost price change is about \$2.72 in a multiple agent model. Aguirregabiria (1999) finds the price adjustment cost per change is between \$0.82 (for price decreases) and \$2.23 (for price increases). These comparisons show that menu costs for Amazon are significantly higher than offline grocery stores and supermarkets. The difference is potentially due to the scale of Amazon's operation and the product category studied. Local grocery stores typically face a stable demand curve for most of their products. The number of competitors is also limited compared to the competition faced by an online retailer that has no geographic bounds. This makes it straightforward for physical grocery stores to make price change decisions, and the majority of the menu costs would be due to the physical labor costs of changing prices. Amazon, on the other hand, faces a national market with large scale operations. The competitive environment is substantially complicated, requiring constant monitoring of hundreds of competitors that include both smaller merchants and larger well established competitors like Barnes and Noble. Moreover, the products in our sample face a fast changing demand curve. Significant volatility in daily demand requires careful analysis from the retailer to tease out long-term changes from the short-term blips. These factors are likely to increase the managerial costs in conducting price analysis and making pricing decisions based on demand and competitive responses.

An important result from our analysis is that despite the high menu costs in absolute terms per price change, they account for a small percentage of Amazon revenue. Dividing the menu costs by the average revenue generated for each price change reveals that menu costs account for only 0.2% of Amazon revenue.<sup>3</sup> This provides another perspective for comparison with earlier studies. Slade (1998) estimates the menu costs of Saltine crackers in a retail supermarket industry and reports that total costs of price adjustment (which includes fixed as well as variable costs) comprise about 2.3 percent of revenue. Levy et. al. (1997) directly measure menu costs in supermarkets and find that menu costs account for about 0.7 percent of total revenue. Golosov and Lucas (2007) use BLS survey data to estimate menu costs across a large number of product categories. They find that menu costs

<sup>2</sup> The regression is performed under the assumption that  $\beta_i$  remains the same across all products. This assumption is used to illustrate the presence of transitory demand changes and for easy exploration. The estimations of equation (15) and (14) are performed allowing all coefficients to vary across products.

<sup>3</sup> We calculate average revenue for each price change as follows. First, we note that a price stays on average for 142 days. The average daily sales are 2.1 units with an average price of \$19.15. Multiplying these numbers reveal that average revenue for each price change is \$5710.

consist of about 0.5% of total revenue. Given the results from studies, our findings suggest that online retailers face lower total menu costs at about 0.2% of total revenue, despite higher menu costs for individual price changes.

## **Discussion and Conclusion**

Price adjustment cost has significant implications for firms' competitive strategy and industry structure. Prior studies have shown both theoretically and empirically that a small price adjustment cost could lead to a high level of price rigidity with important consequences. The main objective of this paper is therefore to empirically estimate the magnitude of menu costs of online retailers that causes price rigidity online. By considering Amazon's price change decisions and estimating the value of price changes, we can identify the magnitude of the price adjustment cost. A key challenge in this approach is that the extent of price change is influenced by the exogenous change in demand, which is not directly observable to researchers. We use statistical processes to identify demand change processes, thus making the magnitude of price adjustment cost empirically identifiable. Specifically, we are able to separate permanent demand changes that affect retailers' price decisions and transitory demand changes that do not affect retailers' price decisions.

Using actual price and demand data from online retailers, we find that two unique characteristics of menu costs for online retailers exist. First, we show that online retailers face substantial menu costs in making individual price changes. This is potentially due to online retailers' nation-wide exposure and complex online competitive environments. Second, we find that online retailers face lower menu costs in aggregate, due to its scale of operation that allows spreading menu costs across large volume of products. The combination of the two characteristics supports the conjecture that online retailers face overall lower menu costs. However, the lower menu costs appear to be mainly due to economies of scale of online retailers, instead of lower costs in making individual price adjustments as hypothesized in earlier studies. Our results provide a first look into menu costs in online retailers and their economic characteristics.

Measuring menu costs for online retailers presents a first step to develop a better understanding of economic behavior and strategic interactions between online retailers. Two streams of future research are promising. First, one can consider the causes of menu costs. Given the lack of need for manually changing prices, most of the menu costs for online retailers appear to be managerial costs. Understanding the nature of such managerial costs can help online retailers to reduce menu costs and be more responsive to competitive changes. Second, one can consider the implications of menu costs on the strategic interactions among online retailers. In particular, a better understanding of menu costs for online retailers can provide insights into the formation of price equilibrium in online markets.

## Appendix

Table 1: Summary Statistics					
Variable	Observations	Mean	Std. Dev.	Min	Max
List Price	562823	24.83	22.86	2.99	299
Sales Price	561349	19.15	21.42	2	299
Sales Rank	561052	178601.2	269875.6	1	3325880
Days from Release	524066	182.51	256.4	-9205	38769
Demand	561052	2.10	18.57	.011	5324.58
Price Change	3732	.029	1.11	-4.61	4.141
Price Change (dummy)	570029	.006	.08	0	1

Table 2: Autoregressive Process of First Difference in Book Demands			
	Coefficient	t-stat	p-value
$\beta_0$	-0.25	-1.93	0.05
$\beta_1$	-0.37	-290.61	<0.001

Table 3: Estimation of Menu Costs			
	Price Change without Censoring	Price Change with Censoring at \$0.10	Price Change with Censoring at \$0.50
Menu cost (g)	11.11	10.97	10.97
	(.01) ***	(.01) ***	(.01) ***
Noise ( $\sigma$ )	0.00	0.00	0.00
	(.00) ***	(.00) ***	(.00) ***
Observations	30199	30199	30199
-2 Log Likelihood	36717	36975	36975

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